# Comparative Analysis of Different Vegetation Indices of Noida City Using Landsat Data

**Richa Sharma, Lolita Pradhan, Maya Kumari, and Prodyut Bhattacharya**

**Abstract** Noida is a part of National Capital Territory (NCT) of Delhi and is rapidly expanding. With high rates of urbanization in the form of skyscrapers, industrialization, and dense population, the city is under enormous pressure. Increasing environmental pollution and waste generation, along with urban heat island effects, has made the city more vulnerable to climate change impacts. Monitoring and studying the urban green cover of the city is one of the solutions to the aggravating challenges. Inputs from such detailed analysis are important for sustainable city planning. The present work explores five spectral indices to study the vegetation status of the city between 2011 and 2019, namely NDBI, GARI, SAVI, GSAVI, and NDVI. Temporal examination of NDBI from year 2011 to 2019 indicates overall rise in the built-up area of the city. The appropriateness of the indices was assessed using six image quality measures like mean absolute deviation (MAD), correlation coefficient (CC), root mean square error (RMSE), standard deviation (SD), ERGAS, and mean absolute percentage error (MAPE), respectively. Quantitative evaluation of the performance of the four vegetation indices was performed on the enhanced images to select the most appropriate vegetation index that can be used to study urban vegetation status. The analysis of the six quality parameters reveals that SAVI is much sensitive to urban greenness than other vegetation indices with respect to urban areas.

**Keywords** NDBI · GARI · SAVI · GSAVI · NDVI

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# 1   Introduction

Cities have always been important centers of human development, commercial activities, technological innovation and home to migrating populations. With rapid conurbation, urban cities are under tremendous stress of environmental pollution, waste management, and limited resources. These problems are further intensified by climate change and its impacts. With proper city planning, urban centers can be managed to help reduce the unwanted consequences of global environmental challenges [6].

Urban vegetation can be an important part of the solution when striving for sustainable development of cities. Urban green spaces help in reducing energy use, reducing burden on fossil fuel-based energy requirement for cooling or heating spaces [8]. These also help in increasing natural infiltration of water into the ground, recharging ground water levels. Urban trees also act as carbon sinks, thereby mitigating impacts of global warming [2]. Apart from these, these green spaces also provide aesthetic and cultural benefits to the city dwellers [5].

Therefore, it is imperative to study and monitor urban vegetation to understand land use/land cover dynamics. Monitoring spatial and temporal changes in vegetation linked with urbanization provides an important input for sustainable city planning. The benefits of the urban green spaces can be maximized when such large-scale analysis is available for the cities to the urban planners.

Remote sensed data is one of the most preferred approaches these days to study terrestrial vegetation and to arrive at solutions for effective urban green space management. Satellite-based remote sensing has several advantages such as cost effectiveness, high spatial resolution, and availability of long time series data. A large body of work exists on several vegetation indices (VI) derived using satellite imageries based on the wavelengths of light absorbed and reflected by vegetation. These indices are used in a number of applications and provide accurate and precise information on vegetation structure and dynamics.

Different indices have been used to assess urban vegetation. Normalized difference vegetation index (NDVI) is one of the most preferred indices to study vegetation cover of an area. Guha et al. [4] used NDVI to study vegetation cover in Raipur city, India. Anchang et al. [1] employed soil-adjusted vegetation index (SAVI) to monitor urban vegetation in an African city. Scudiero et al. [10] applied the green atmospherically resistant index (GARI) to assess vegetation in Western San Joaquin Valley, California, USA.

The first objective of the present work is to study five spectral indices for Noida city, namely normalized difference built-up index (NDBI), green atmospherically resistant index (GARI), soil-adjusted vegetation index (SAVI), green soil-adjusted vegetation index (GSAVI), and normalized difference vegetation index (NDVI). The second objective is to highlight the most appropriate index that can be used for studying urban vegetation using different image quality parameters.

## 2   Study Area

New Okhla Industrial Development Authority abbreviated as Noida is under the district of Gautam Buddha Nagar, Uttar Pradesh (Fig. 1). Noida was formulated by Uttar Pradesh government on April, 19, 1976 which is now a part of National Capital Territory (NCT) of Delhi.

The latitudinal and longitudinal extension of this city is 28.57 °N 77.32 °E. The city is surrounded by two rivers—Yamuna river in north and northwest and Hindon river in northeast, east, and southeast of the city. The hot and dry climatic weather condition is found in Noida city where temperatures range between maximum 45 °C and minimum 28 °C. From June to September month monsoons are generally predominated. Because of the cold waves of Himalayan Regions, winters are very cold here and the maximum and minimum temperature varies from 3 to 10 °C.

Every year huge amount of money is spent for the development of the city. After Mumbai, Noida is famous for its skyscrapers. Noida is highly integrated town where it offers residential, commercial, and industrial structure. In the last 10 years, Noida has also become a hub of different software and hardware companies and is well connected by metro, rail, and road.

## 3   Data and Methods

The general methodology of the paper is illustrated through Fig. 2.

### 3.1   Satellite Data

The details of the remote sensed data is given in Table 1.

### 3.2   Image Preprocessing

The Landsat images of 2011 and 2019 were used as primary data for deriving spectral indices. The temporal images were recorded under uniform atmospheric condition and image preprocessing was applied before processing spectral indices.
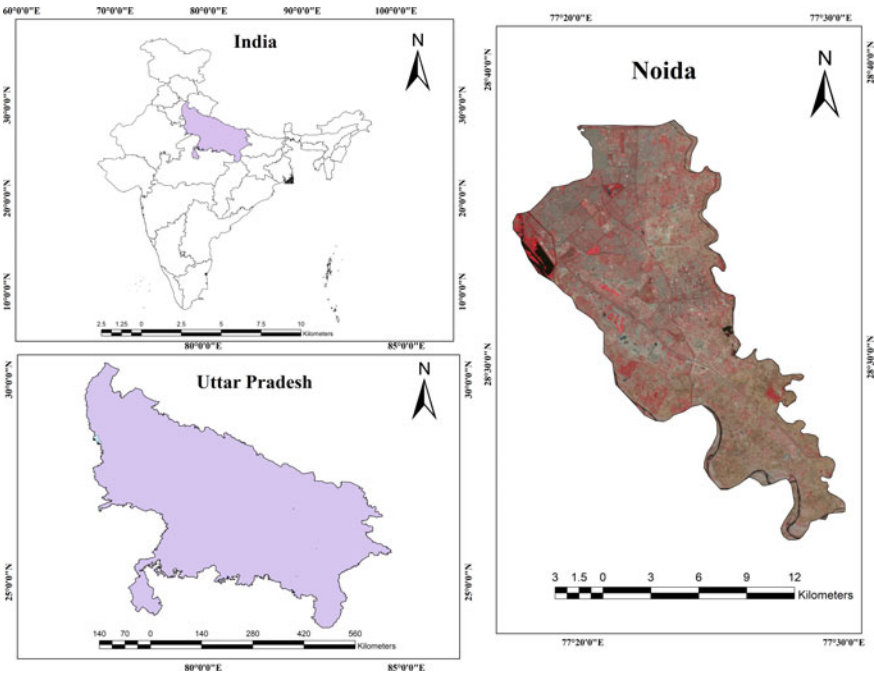
**Fig. 1** Study area map

**Table 1** Satellite data

| S. N. | Data type | Acquisition date | Source |
|---|---|---|---|
| 1 | LANDSAT 4-5TM | 16 January, 2011 | USGS |
| 2 | LANDSAT 8 OLI | 23 February, 2019 | USGS |

## 3.3 Spectral Indices

Spectral indices aid in distinguishing between various types of land cover. A vegetation index provides both quantitative as well as qualitative evaluation of vegetation density of an area. There are variety of such different indices that measure wavelength of the incoming solar insolation in visible as well as near-infrared portion of the spectrum and quantify vegetation biomass for each pixel in the satellite imagery. A detailed analysis of the spectral response for a vegetation class can also be used to distinguish between healthy and stressed vegetation. The present work limits to analysis of the following five spectral indices:

- Normalized difference built-up index (NDBI)
- Green atmospherically resistant index (GARI)
- Green soil-adjusted vegetation index (GSAVI)

- Soil-adjusted vegetation index (SAVI)
- Normalized difference vegetation index (NDVI).

### 3.3.1 Normalized Difference Built-Up Index (NDBI)

Normalized difference built-up index (NDBI) is a spectral index that highlights the built-up area and ranges from $+1$ to $-1$ [18]. NDBI is derived using the below equation, where SWIR is short-wave infrared, and NIR is near-infrared spectral band.

$$NDBI = (SWIR - NIR)/(SWIR + NIR)$$

### 3.3.2 Green Atmospherically Resistant Index (GARI)

Green atmospherically resistant index (GARI) is highly responsive to chlorophyll concentrations and can counter the effects of atmospheric interference in satellite imagery [3]. GARI is derived using the below equation, where NIR is near-infrared, GREEN is the green, BLUE is the blue, and RED is red spectral band of the dataset.

$$GARI = \{NIR - [Green - (Blue - Red)]\} / \{NIR + [Green - (Blue - Red)]\}$$

### 3.3.3 Soil-Adjusted Vegetation Index (SAVI)

SAVI is used for monitoring both soil and vegetation. NDVI and SAVI are almost the similar indices but the difference is that SAVI is used for only low vegetation coverage of less than 40%. The formula of SAVI is

$$SAVI = [(NIR - Red) / (NIR + Red + L)] * (1 + L)$$

where $L = 0.5$ where $L$ is a correction factor that ranges from 0 (very high vegetation) to 1 (very low vegetation) [16]. The value 0.5 is for intermediate vegetation cover which is used in the present work. NIR is near-infrared and RED is the red spectral band of the dataset.

### 3.3.4 Green Soil-Adjusted Vegetation Index (GSAVI)

Green soil vegetation index (GSAVI) is similar to SAVI where the vegetation is highlighted. This index was designed with color infrared photography for the nitrogen estimation [13]. The formula of GSAVI is

$$\text{GSAVI} = \big[(\text{NIR} - \text{green})\,/\,(\text{NIR} + \text{green} + \text{L})\big] * (1 + \text{L}), \text{ where } \text{L} = 0.5$$

NIR is near-infrared and GREEN is the green spectral band of the dataset. *L* is a correction factor that ranges from 0 (very high vegetation) to 1 (very low vegetation).

### 3.3.5 Normalized Difference Vegetation Index (NDVI)

In normalized difference vegetation index (NDVI), NIR band reflects the vegetation strongly and red band absorbs the vegetation. NDVI ranges between $-1$ and $+1$ and the values which are very close to $+1$ there is a high possibility of dense vegetation and the value is near to $-1$, it indicates no vegetation [9]. NDVI uses the ratio of red (*R*) and near-infrared (NIR) spectral bands

$$\text{NDVI} = (\text{NIR} - \text{Red})\,/\,(\text{NIR} + \text{Red})$$

## 3.4 Image Quality Measures

The appropriateness of the indices was judged using six quality indicators like mean absolute deviation (MAD), correlation coefficient (CC), root mean square error (RMSE), ERGAS, standard deviation (SD), and mean absolute percentage error (MAPE), respectively [11] (Table 2).

All the spectral indices were derived using ArcGIS10.1 software. The enhanced images values were examined using six statistical parameters in reference to the standard false color composite (FCC) values.

## 4 Results and Discussion

In recent decades, exponentially expanding population and urbanization has prompted an unplanned and unsustainable urban sprawl, an emerging major threat in Noida. The dynamic nature of urban growth makes it little difficult to measure greenness extent around it. Temporal examination of NDBI from year 2011 to 2019 indicated overall rise in the built-up area. In 2011, the NDBI value ranged between $-0.43$ and $0.44$ while in 2019 the maximum value reached to 0.66 indicating huge expansion of urban area. By 2011, almost whole of northern and central Noida got urbanized. However, in 2019 most of southern part of Noida which is agricultural area is in process of urban development and areas along the Noida Expressway have urbanized [11].

The green space in urban area are like lungs of the city as they support exchange of gases and keeps microclimate cooler. The remote sensing-based spectral indices

**Table 2** Image quality indicators

| S. N | Quality indicator | Mathematical expression | Interpretation |
|---|---|---|---|
| 1 | Mean absolute deviation (MAD) | $\text{MAD} = \frac{\sum_{t=1}^{n}|A_t - F_t|}{n}$ <br> Where $A_t$ and $F_t$ are the pixel values of the original and enhanced image, respectively, and $n$ is the number of observations | Image is of better quality when MAD values are less |
| 2 | Correlation coefficient ($C_C$) | $C_c = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$ <br> Where $x_i$, $y_i$ are the gray values of homologous pixel synthesized image and real high-resolution image [7] | Values range between 0 and 1. $C_C$ equal to 1 implies that both images are same, value corresponding to 0 implies they are dissimilar and value corresponding to $-1$ implies a negative correlation |
| 3 | Root mean square error (RMSE) | $\text{RMSE} = \sqrt{\sum \frac{(y_{\text{pred}} - y_{\text{ref}})^2}{N}}$ <br> Where $Y_{\text{pred}}$ is the gray value of the enhanced image and $Y_{\text{ref}}$ is the gray value of the original image. $N$ is the no. of observations | Values on the lower side indicate a good fit with minimum errors |
| 4 | ERGAS | $\text{ERGAS} =$ <br> $100\frac{h}{l}\sqrt{\frac{1}{n}\sum_{i-1}^{n}\left(\frac{\text{RMSE}}{\text{Mean}}\right)^2}$ <br> Where $h$ and $l$ are spatial resolution of Reference and Enhanced images, respectively; N is the number of bands | Higher values indicate aberration, whereas lower values indicate no distortion in the two images |
| 5 | Standard deviation (SD) | $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$ <br> Where $x_i$ is the data vector and x is the mean value and $N$ is the total number of observations | Image is of better quality when SD values are less |
| 6 | Mean absolute percentage error (MAPE) | $\text{MAPE} = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} X 100$ <br> Where $A_t$ and $F_t$ are the pixel values of the original and fused image, respectively, and $N$ is the total number of observations | Image is of better quality when MAPE values are less |

**Table 3** Descriptive statistics of vegetation indices

|  | GARI | | GSAVI | | SAVI | | NDVI | |
|---|---|---|---|---|---|---|---|---|
|  | 2011 | 2019 | 2011 | 2019 | 2011 | 2019 | 2011 | 2019 |
| Minimum | −1.03 | −2.99 | −0.24 | −0.33 | −0.34 | −0.36 | −0.23 | −0.24 |
| Maximum | 0.98 | 0.98 | 0.41 | 0.49 | 0.72 | 0.84 | 0.48 | 0.56 |
| Mean | 0.91 | 0.95 | 0.38 | 0.43 | 0.69 | 0.78 | 0.42 | 0.51 |

discriminate between the vegetation and non-vegetation. But in areas like Noida where mixed pixels of urban and vegetation are common, it is very difficult to study vegetation. Therefore, certain constants or adjustment factors are applied to suppress the reflectance of other land uses and highlight vegetation cover.

The statistics of various indices used in the study is summarized below (Table 3).

## 4.1  Analysis of Image Quality Measures

Multispectral images of Landsat were enhanced with respect to vegetation using NDVI, SAVI, GSAVI, and GARI, with an objective to select the most appropriate vegetation index that can be used to study urban vegetation. The corresponding maps of various spectral indices are demonstrated in Figs. 3, 4, 5, 6 and 7. Qualitative evaluation (i.e., ocular interpretation) may not be always sufficient for final assessments as it may include aberrations that cannot be just discriminated visually [17]. Therefore, it is imperative to quantitatively assess images and respective indices. The six quality indicators (Table 2) were employed to all the images, and the results are recorded in Table 4. These indices were equated and evaluated using RMSE, MAD, CC, ERGAS, SD, and MAPE between FCC (green, red, and NIR) of the multispectral image and enhanced images through vegetation indices [13].

The results indicate highest correlation coefficient of the NDVI image indicating similarity between the reference and the enhanced image. For all other indicators, lower values imply better image quality. Values of RMSE, ERGAS [15], MAPE, SD, and MAD on the lower side suggest line of best fit, with minimum errors. The results indicate that SAVI is much sensitive to urban greenness than other vegetation indices, viz. GSAVI, GARI, and NDVI with respect to urban areas.

## 5  Conclusion

To delineate vegetation using remotely sensed data in an urban region, which is very often affected by the mixed pixels because of the dense built-up, especially city like Noida requires atmospheric correction. The vegetation spectral indices can provide a useful aid to monitor vegetation status at various scales. The present results indicate
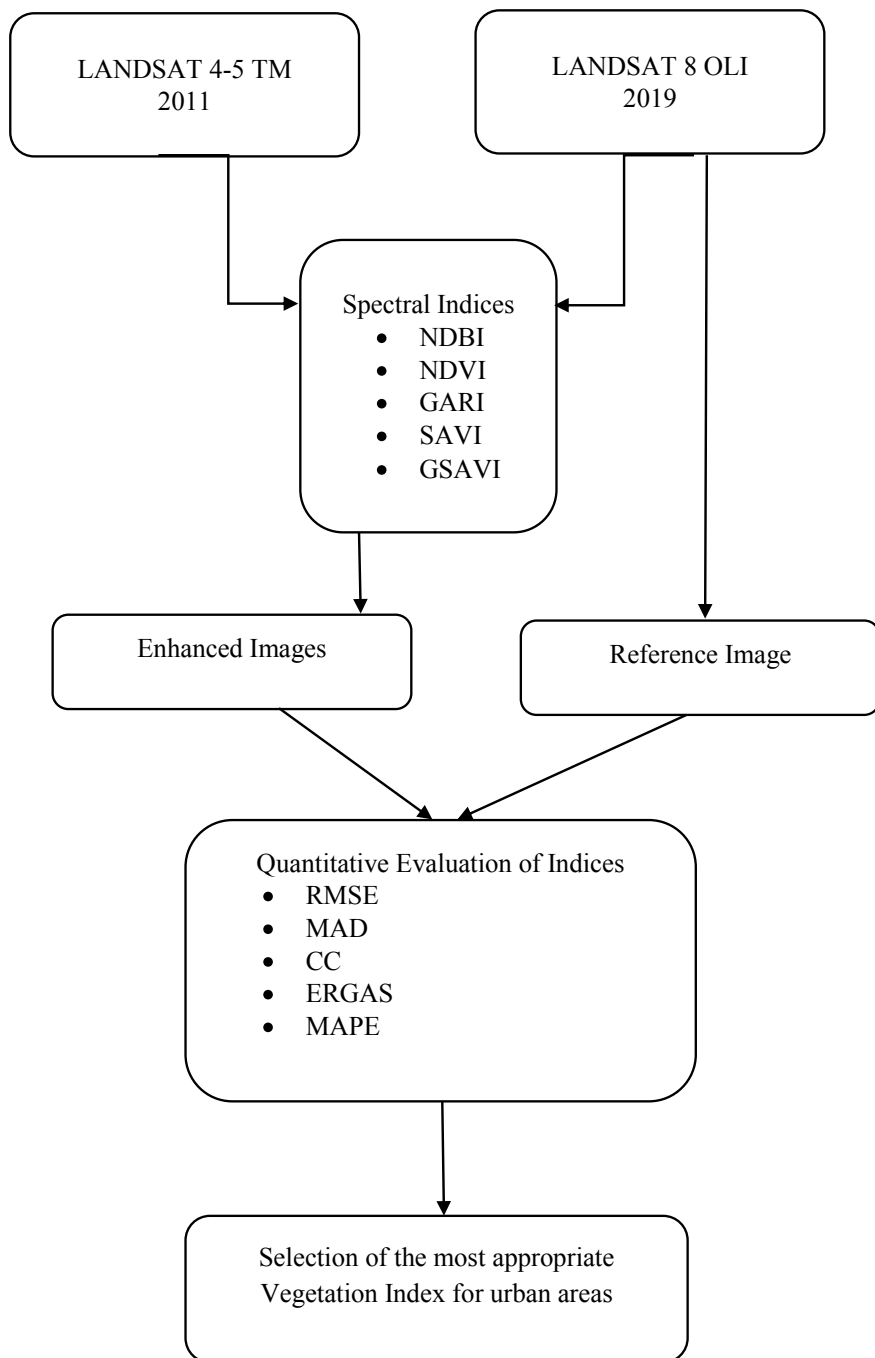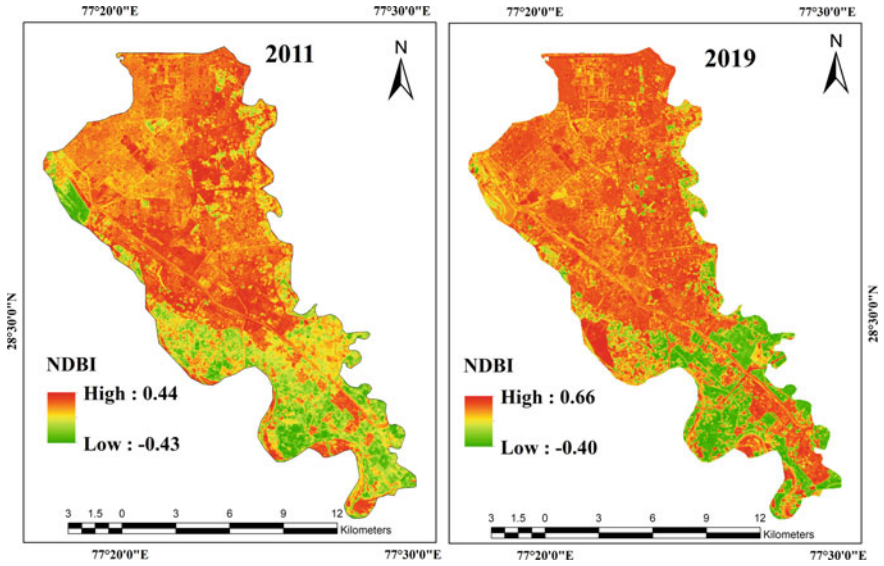
**Fig. 2** Methodology flowchart

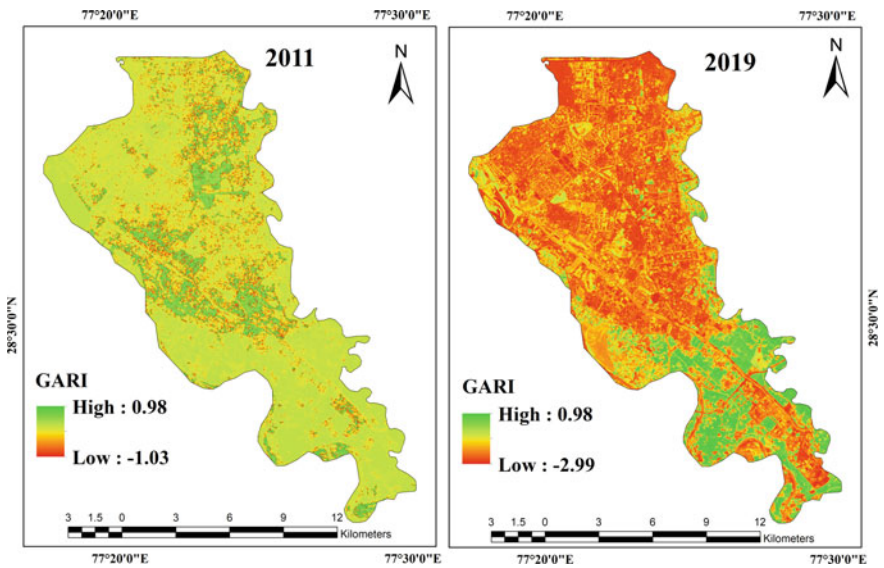**Fig. 3** Normalized difference built-up index map (NDBI)



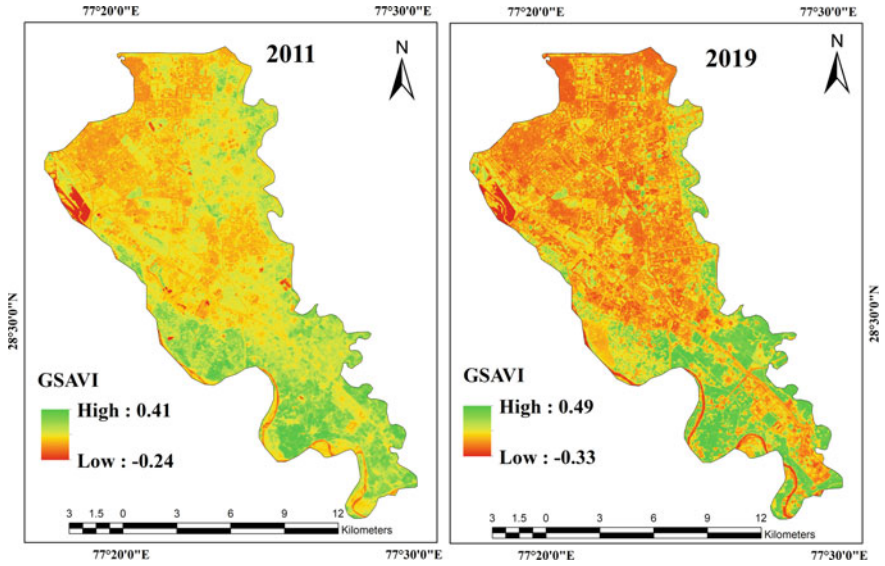**Fig. 4** Green atmospherically resistant index map (GARI)

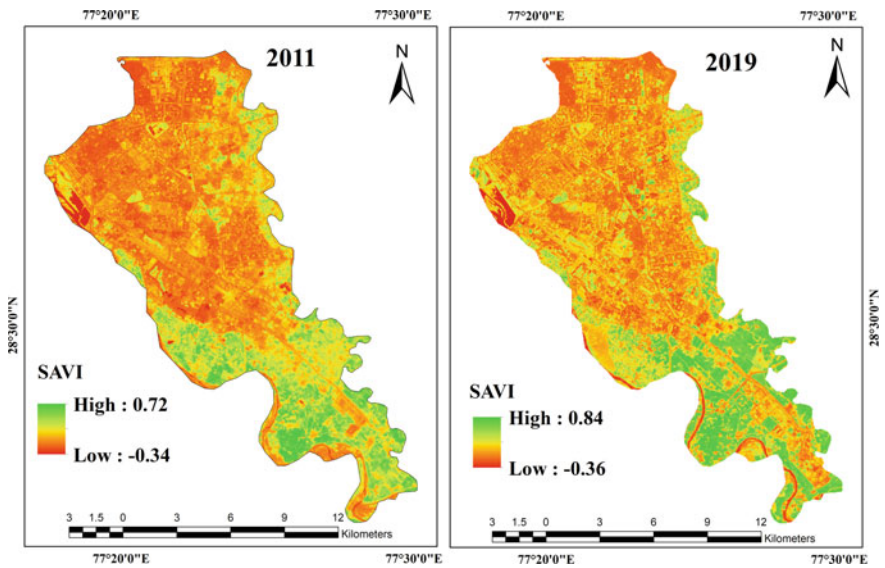**Fig. 5** Green soil-adjusted vegetation index map (GSAVI)



**Fig. 6** Soil-adjusted vegetation index map (SAVI)

**Table 4** Comparison results of enhanced images

| Vegetation indices | RMSE | MAD | CC | ERGAS | SD | MAPE |
|---|---|---|---|---|---|---|
| NDVI | 9779.34 | 9777.52 | 0.567 | 865,565.48 | 0.06 | 0.20 |
| SAVI | 9779.08 | 9777.24 | 0.0116 | 577,048.45 | 0.00 | 0.00 |
| GARI | 9779.62 | 9777.81 | −0.5942 | 36,710,268.29 | 0.09 | 0.298 |
| GSAVI | 9779.34 | 9777.56 | 0.1418 | 996,634.40 | 0.05 | 0.181 |
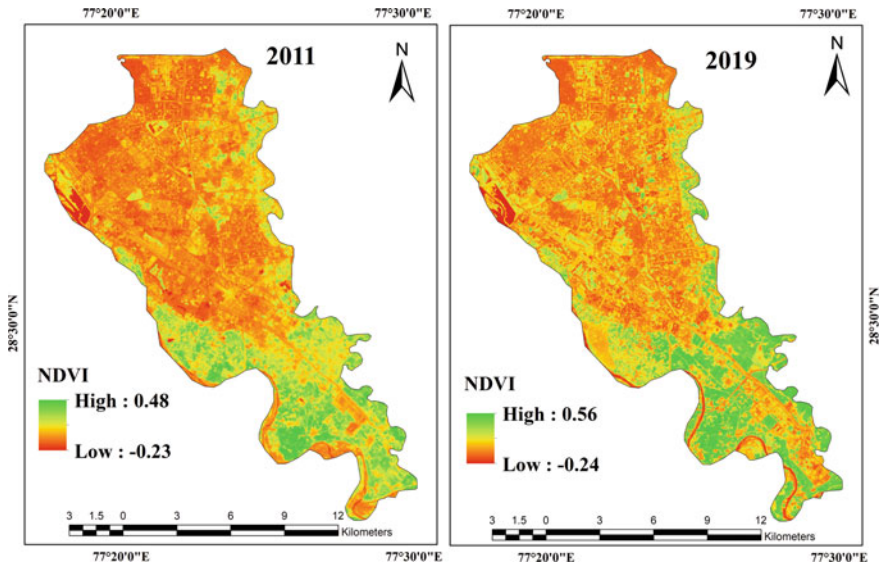


**Fig. 7** Normalized difference vegetation index map (NDVI)

that SAVI is one of the most appropriate indicators of assessing and monitoring urban vegetation. SAVI is less sensitive to other land uses such a built-up and soil as compared to other vegetation indices.

# References

1. Anchang JY, Ananga EO, Pu R (2016) An efficient unsupervised index based approach for mapping urban vegetation from IKONOS imagery. Int J Appl Earth Obs Geoinf 50:211
2. Chen WY (2015) The role of urban green infrastructure in offsetting carbon emissions in 35 major Chinese cities: a nationwide estimate. Cities 44:112–120
3. Gitelson A, Kaufman Y, Merzylak M (1996) Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sens Environ 58:289–298
4. Guha S, Govil H, Mukherjee S (2017) Dynamic analysis and ecological evaluation of urban heat islands in Raipur city India. J Appl Remote Sensing 11(3):36020

5. Huang L, Li J, Zhao D, Zhu J (2008) A fieldwork study on the diurnal changes of urban microclimate in four types of ground cover and urban heat island of Nanjing China. Building Environ 43(1):7–17
6. Hunt A, Watkins P (2011) Climate change impacts and adaptation in cities: a review of the literature. Climatic Change 104:13–49
7. Karathanassi V, Kolokousis P, Ioannidou S (2007) A comparison study on fusion methods using evaluation indicators. Int J Remote Sens 28(10):2309–2341
8. Nowak DJ, Greenfield EJ (2018) Declining urban and community tree cover in the United States. Urban Forest Urban Greening 32:32–55
9. Rouse JW (1974) Monitoring the vernal advancement of retrogradation of natural vegetation. NASA/GSFG Type III Final Report 371
10. Scudiero E, Skaggs TH, Corwin DL (2014) Regional scale soil salinity evaluation using Landsat 7, Western San Joaquin Valley, California, USA. Geoderma Reg 2:82–90
11. Sharma R, Pradhan L, Kumari M, Bhattacharya P (2021) Assessing urban heat islands and thermal comfort in Noida City using geospatial technology. Urban Clim 35:100751
12. Somvanshi SS, Kunwar P, Tomar S, Singh M (2017) Comparative statistical analysis of the quality of image enhancement techniques. Int J Image Data Fusion 9(2):131–151
13. Somvanshi SS, Kumari M (2020) Comparative analysis of different vegetation indices with respect to atmospheric particulate pollution using sentinel data. Appl Comput Geosci 100032
14. Sripada RP, Heiniger RW, White JG, Meijer AD (2006) Aerial colour infrared photography for determining early in-season nitrogen requirements in corn. Agron J 98(4):968–977
15. Wald L (2000) Quality of high resolution synthesised images: Is there a simple criterion? In: Ranchin T, Wald L (eds) Proceedings of the third conference "fusion of earth data: merging point measurements, raster maps and remotely sensed images. Sophia Antipolis, France, January 26–28, 2000, published by SEE/URISCA, Nice, France, 99–103
16. Xue J, Su B (2017) Significant remote sensing vegetation indices: a review of developments and applications. J Sensors 17
17. Yilmaz V, Gungor O (2016) Determining the optimum image fusion method for better interpretation of the surface of the Earth. Norwegian J Geograp 70(2):69–81
18. Zha Y, Gao J, Ni S (2003) Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. Int J Remote Sens 24(3):583–594